

Q1

a) Because x, y are independent

$$p(\mu, \pi | x, y) = p(\mu | x) p(\pi | y)$$

According to bayes rule

$$\begin{aligned}
p(\mu | x) &= \frac{p(x | \mu) p(\mu)}{\int p(x | \mu) p(\mu) d\mu} \\
&= \frac{e^{-\frac{\lambda(x-\mu)^2}{2}} e^{-\frac{\gamma\mu^2}{2}}}{\left(\frac{\lambda + \gamma}{2\pi}\right)^{-\frac{1}{2}}} \\
&= \left(\frac{\lambda + \gamma}{2\pi}\right)^{\frac{1}{2}} e^{-\frac{(\lambda + \gamma)\left(\mu - \frac{\lambda x}{\lambda + \gamma}\right)^2}{2}} = \text{Normal}\left(\frac{\lambda x}{\lambda + \gamma}, (\lambda + \gamma)^{-1}\right)
\end{aligned}$$

For $p(\pi | y)$

$$\begin{aligned}
p(\pi | y) &= \frac{p(y | \pi) p(\pi)}{\int p(y | \pi) p(\pi) d\pi} \\
&= \frac{1}{B(\alpha')} \prod_{k=1}^3 \pi(k)^{\alpha_k - 1 + 1(y=k)} = \text{dirichlet}(\alpha') \\
\alpha' &= \{\alpha_k + 1(y = k)\}
\end{aligned}$$

Therefore

$$p(\mu, \pi | x, y) = \left(\frac{\lambda + \gamma}{2\pi}\right)^{\frac{1}{2}} e^{-\frac{(\lambda + \gamma)\left(\mu - \frac{\lambda x}{\lambda + \gamma}\right)^2}{2}} * \frac{1}{B(\alpha')} \prod_{k=1}^3 \pi(k)^{\alpha_k - 1 + 1(y=k)}$$

b) According to the note and independence

$$p(x_2, y_2 | x_1, y_1) = \int p(x_2 | \mu) p(\mu | x_1) d\mu * \int p(y_2 | \pi) p(\pi | y_1) d\pi$$

by using the outcome from part a, we can calculate the integral

$$\begin{aligned}
\int p(x_2 | \mu) p(\mu | x_1) d\mu &= \left(\frac{\lambda(\lambda + \gamma)}{2\pi}\right)^{\frac{1}{2}} \exp\left\{-\frac{\lambda}{2}x_2^2 + \frac{\lambda^2(x_1 + x_2)^2}{2(2\lambda + \gamma)} - \frac{\lambda^2x_1^2}{2(\lambda + \gamma)}\right\} \\
\int p(y_2 | \pi) p(\pi | y_1) d\pi &= \frac{\prod_{k=1}^3 (\alpha_k + 1(y_1 = k))^{1(y_2 = k)}}{\sum_{i=1}^3 (\alpha_i) + 1}
\end{aligned}$$

Therefore

$$p(x_2, y_2 | x_1, y_1) = \left(\frac{\lambda(\lambda + \gamma)}{2\pi}\right)^{\frac{1}{2}} \exp\left\{-\frac{\lambda}{2}x_2^2 + \frac{\lambda^2(x_1 + x_2)^2}{2(2\lambda + \gamma)} - \frac{\lambda^2x_1^2}{2(\lambda + \gamma)}\right\} \frac{\prod_{k=1}^3 (\alpha_k + 1(y_1 = k))^{1(y_2 = k)}}{\sum_{i=1}^3 (\alpha_i) + 1}$$

Q2

According to the note

$$\begin{aligned}
q(c) &= p(c | \lambda, x) \\
&= \frac{p(x | \lambda, c) p(c)}{\int p(x | \lambda, c) p(c) dc} \\
&\propto e^{-\lambda c} \frac{\lambda^x}{x!} \theta_c
\end{aligned}$$

$$\lambda_i = \arg \max_{\lambda_i} L(\lambda) = x$$

EM algorithm

1. Initializing λ_0 in some way
2. For iteration $t = 1, 2, \dots, T$
 - (a) E-step: Calculate $E = E_{q_t}[c]$, where

$$E_{q_t}[c] = \sum_{i=1}^k e^{-\lambda_{i(t-1)}} \frac{\lambda_{i(t-1)}^x}{x!} \theta_{i(t-1)} i$$

- (b) M-step: Update vector λ using the expectations above in the following equations

$$\lambda_i = x$$

- (c) Calculate $\ln p(x|\lambda)$ using the equation

$$\ln p(x|\lambda_t) = \ln e^{-\lambda_t} \frac{\lambda_t^x}{x!}$$

Here λ_t is one dimension of λ_t vector, since every dimension is the same

Q3

According to the note:

$$q(\theta) \propto \exp\{E_{q(\lambda_1, \dots, \lambda_n)}[\ln p(x|\lambda) + \ln p(\lambda|\theta) + \ln p(\theta)]\}$$

$$\propto \exp\left\{\sum_{i=1}^n E_q[\ln p(\lambda_i|\theta)]\right\} p(\theta)$$

$$\propto \theta^{na+b-1} e^{-(\sum_{i=1}^n E_q[\lambda_i] + c)\theta} = \text{Gamma}(b', c')$$

$$b' = na + b, \quad c' = \sum_{i=1}^n E_q[\lambda_i] + c$$

$$q(\lambda_i) \propto \exp\{E_{q(\theta)} \prod_{j \neq i} q(\lambda_j) [\ln p(x|\lambda) + \ln p(\lambda|\theta) + \ln p(\theta)]\}$$

$$\propto \exp\left\{\sum_{i=1}^n E_q[\ln p(\lambda_i|\theta)] + E_q[\ln p(x_i|\lambda)]\right\}$$

$$\propto \lambda_i^{x_i+a} e^{-(E_q[\theta]+1)\lambda_i} = \text{Gamma}(a', \theta')$$

$$a' = a + x_i, \quad \theta' = E_q[\theta] + 1$$

Inputs: Data and definitions $q(\theta) = \text{Gamma}(b', c')$ and $q(\lambda_i) = \text{Gamma}(a', \theta')$

Outputs: Values for b', c', a', θ'

1. initialize $b'_0, c'_0, a'_0, \theta'_0$ in some way
2. For iteration $t = 1, \dots, T$
 - Update $q(\theta)$ by setting

$$b' = na + b, \quad c' = \sum_{i=1}^n \frac{a'_{i(t-1)}}{\theta'_{t-1}} + c$$

Update $q(\lambda_i)$ by setting

$$a' = a + x_i, \quad \theta' = \frac{b'_{t-1}}{c'_{t-1}} + 1$$

Evaluate $\mathcal{L}(b'_t, c'_t, a'_t, \theta'_t)$ to access convergence

$$L(b'_t, c'_t, a'_t, \theta'_t) = E_q[\ln(x, \lambda, \theta)] - E_q[\ln q(\lambda)] - E_q[\ln q(\theta)]$$

$$\begin{aligned}
&= \sum_{i=1}^n (x_i(\psi(a'_i) - \ln \theta') - \ln x_i! - \frac{a'_i}{\theta'}) + na(\psi(b') - \ln c') - n \ln \Gamma(a) - n(a-1) \ln \theta' \\
&\quad + \sum_{i=1}^n ((a-1)\psi(a'_i) - \frac{a'_i b'}{\theta' c'}) + b \ln c - \ln \Gamma(b) + (b-1)(\psi(b') - \ln c') - \frac{cb'}{c} \\
&\quad - n \ln \theta' + \sum_{i=1}^n (a'_i + \ln \Gamma(a'_i) + (1-a'_i)\psi(a'_i)) + b' - \ln c' + \ln \Gamma(b') \\
&\quad + (1-b')\psi(b')
\end{aligned}$$